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Intertemporal Preferences and the Adoption Decision for Bluetooth Speakers

Daniel Guhl* and Daniel Klapper†

December 12, 2019

Abstract

The adoption decision for durable goods is intertemporal by definition. However, estimating utility and discount functions from revealed preference data using dynamic discrete choice models is difficult because of an inherent identification problem. To overcome this issue, we use stated preference data. Specifically, we employ the experimental design of Dubé, Hitsch, and Jindal (2014), where future prices are known and that elicits intertemporal adoption decisions for Bluetooth speakers in a discrete choice framework. We estimate several models of discounting (e.g., static, myopic, geometric, and quasi-hyperbolic) and find considerably lower discount factors than typical market interest rates would suggest. The values are also smaller compared to respondents' matching-based discount factors, even though the correlation is positive and significant. Furthermore, there are substantial differences in discounting across respondents (i.e., heterogeneity in time-preferences) and lastly, there is no strong empirical evidence for quasi-hyperbolic discounting. Thus, the standard economic model seems to be appropriate for the data at hand.

Keywords: Intertemporal preferences, Dynamic discrete choice models, Durable goods adoption

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1 Introduction

Understanding the adoption decision for a durable good is of great importance in quantitative marketing and economics (Nair, 2007; Gowrisankaran and Ryzman, 2012; Melnikov, 2013). Adopting a new product is a dynamic decision problem because deciding if and when to adopt depends on (static) preferences for the product, the discounted future utility flow, and expectations about future market conditions. Dynamic discrete choice models are well suited for studying such adoption decisions, but they suffer from a fundamental identification problem if estimated from market (i.e., revealed preference) data (Magnac and Thesmar, 2002), where utility functions, discount factors, and subjective beliefs about future market conditions are (typically) not jointly identified. As a simple solution, researchers often fix the discount factor in the estimation at a "reasonable value" (Gowrisankaran and Ryzman, 2012). Recently, Dubé, Hitsch, and Jindal (2014; henceforth DHJ) presented a new approach for jointly estimating discount and utility functions from stated choice data. The authors propose a novel design for a discrete choice experiment, where future prices of products are given (i.e., no uncertainty about future market conditions). In several choice scenarios, respondents state (given current and future prices) if they would adopt a new durable good and, if so, when and which particular alternative they would choose. This information enables the joint identification of discount and utility functions.

We apply the approach of DHJ and analyze the adoption decisions for portable Bluetooth speakers over the next three years. The experimental design also allows for a model-free within-subject analysis of the intertemporal adoption decisions. We estimate several discounting models (e.g., static, myopic, geometric, and (quasi-)hyperbolic) and test whether consumers are forward-looking and, if so, how they value the future. Given limited empirical results on intertemporal preferences in the context of durable good adoption decisions, our effort here can be viewed as a conceptual replication of DHJ. Analyzing a different product category with data from a different sample, we aim at a better understanding of how consumer value time. Furthermore, we also measure discount factors using matching-tasks, where the same respondents were told to imagine that they had won money and could get it now or later, and they had to state how much (more) money they would like to receive to wait for one, two, or three years

(Thaler, 1981). This enables us to study differences in discount factors across methods (and respondents) to further improve our understanding about the novel approach proposed by DHJ to elicit intertemporal preferences.

Our results show that consumers are indeed forward-looking, that models with discounting fit the data better than static discrete choice models or models assuming myopic consumers, but that discount factors are considerably lower (on average 0.43) than typical market interest rates would suggest. The estimated discount factors are also lower compared to respondents' matching-based discount factors for comparable monetary values and time frames, but the correlation is positive and statistically significant, which speaks for the validity of the approach of DHJ. As in DHJ, we also find substantial differences in discounting across respondents (i.e., heterogeneity in time-preferences), and this means that models using a homogeneous discount factor might lead to biased results and false implications. Lastly, we do not find strong empirical evidence for quasi-hyperbolic discounting and, therefore, the standard economic model seems to be appropriate for the data at hand.

The remainder of the paper is organized as follows: In section 2, we briefly present the discrete choice models and the different discount functions we employ in our empirical study. The setup for our empirical study is discussed in section 3. In section 4, we summarize the estimation results for multiple models and compare the estimated discount factors with the matching-based discount factors. We conclude in section 5 with a summary of our key findings and an outlook on future research avenues.

2 Model

The model in our analysis captures the inherently dynamic choice problem that consumers face when making adoption decisions for durable goods. That is, consumers interested in the product category have to decide whether they want to adopt the product now or later. Adopting now has immediate benefits (i.e., being able to use the product), but waiting might be beneficial if prices will be lower in the future, which is a reasonable assumption for many durable goods categories (e.g., consumer electronics).

2.1 Discrete Choice Model

Assuming price predictions for all brands $j = 1, \ldots, J$ to be known to all decision makers (i.e., respondents) $i = 1, \ldots, I$ simplifies the problem considerably (see DHJ for more details): For each choice task $c = 1, \ldots, C$, respondent i can either state that she adopts brand j in period $t \leq T$ ($y_i = (j,t)$), or not ($y_i = 0$).

We start with a simple linear additive utility function:

$$u_{ijt} = \gamma_{ij} + \kappa_i \cdot price_{jt}, \tag{1}$$

where γ_{ij} are intercepts for each brand j and κ is the price coefficient. All parameters are respondent-specific. The value in $t = 0$ from adopting the brand j in t is:

$$\omega_{ijt} = f_i(t) \cdot (\gamma_{ij} + \kappa_i \cdot price_{jt}). \tag{2}$$

The discount function $f_i(t)$ maps the net utility u_{ijt} from the adoption decision at time t to the time when the choice experiment takes place ($t = 0$). Adding an i.i.d. type I extreme value distributed error term ε_{ijt} to ω_{ijt} leads to a simple multinomial logit model with $J \cdot T + 1$ alternatives, where the probability of adopting brand j in t is:

$$Pr(y_i = (j,t) | price_{jt}, \theta_i) = \frac{\exp(\omega_{ijt})}{1 + \sum_{t'}^{T} \sum_{j'}^{J} \exp(\omega_{it'j'})}. \tag{3}$$

with $\theta_i = [\gamma_{i1}, ..., \gamma_{iJ}, \kappa_i, \delta_i]' \sim MVN(\bar{\theta}, \Sigma)$.

2.2 Discount Functions

Several discount functions $f_i(t)$ have been proposed in the literature (Urminsky and Zauberman, 2016). The standard economic model assumes geometric discounting (Samuelson, 1937): $f_i^G(t) = \delta_i^t$. In this model the instantaneous discount rate, which is defined as $-f_i'(t)/f_i(t)$, is $-\log(\delta)$ and hence constant. The model further nests two important special cases: The static model, where $\delta_i = 1$ and the myopic model with $\delta_i = 0$. In the former case, consumers do not discount the future at all and are infinitely patient. In the latter case, consumers discount the future as extreme as possible and obtain no utility from the adoption in $t > 0$.

The hyperbolic model of Mazur (1987), with $f_i^H(t) = 1/(1+\alpha_i \cdot t)$, relaxes the assumption of constant instantaneous discount rates. However, the single model parameter α is difficult to interpret because it reflects both, the change in the discount rate over time as well as the average discount rate. Another popular model in economics is the hyperbolic discounting model (Laibson, 1997): $f_i^{QH}(t) = \beta_i \cdot \delta_i^t$, with $f_i^{QH}(0) = 1$. Here, β_i represents the present bias of consumers, allowing for lower discount factors after $t = 1$.

2.3 Identification and Estimation

Each respondent provides multiple choices for several price scenarios (i.e., choice tasks), leading to a panel structure of the data. Figure 1 shows an example of a price scenario as it was used in the experiment. Each scenario (see the appendix for a summary of all price scenarios) is different and provides relevant information for estimating the models. DHJ show that the variation in current and future market conditions is sufficient for the joint identification of the discounting and utility functions. The simple intuition is that varying prices in this setup should not only affect which brand is chosen but also when. A lower future price can, ceteris paribus, lead to adoptions at a later period. On the other hand, a lower earlier price can, ceteris paribus, lead to adoptions at an earlier period. We discuss this in greater detail when we present a model-free analysis of the data in section 3.

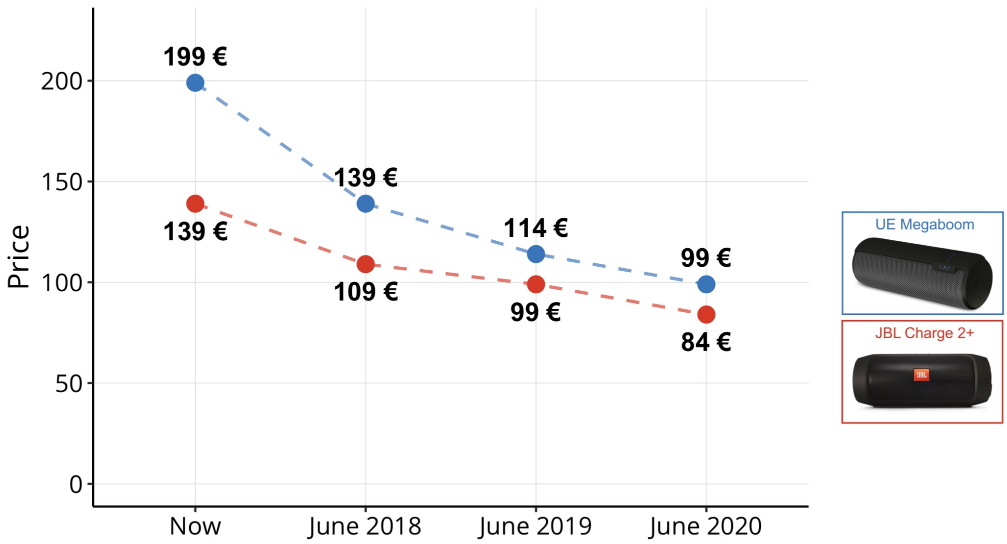

Figure 1: Example Price Scenario

The models are estimated using maximum simulated likelihood (Train, 2009). In case parameters are bounded (e.g., $\delta_i \in (0,1)$), we transform the corresponding parameters in θ_i accordingly (e.g., logistic). 1,000 Halton draws are used in the estimation to approximate the integrals in the likelihood function. We tested multiple starting values and checked the final Hessian at convergence. Individual-level parameters are estimated via the "approximate Bayesian" approach described in Train (2009, ch. 11).

3 Empirical Setup and Data Description

We created an online survey using Sawtooth that included the experimental price variation. As mentioned earlier, we are interested in the adoption decision of portable Bluetooth speakers (see figure 1). At the time of the data collection (June 2017), this product category was reasonably new, but already popular, in particular, with younger consumers. We included the two most prominent brands, UE (Megaboom) and JBL (Charge 2+), and explained to the respondents that the prices are predictions of experts that they should interpret as given (i.e., without uncertainty). In line with the real market (at that time), the prices of UE are higher than the prices of JBL. Furthermore, as usual for consumer electronics, all future prices are decreasing, providing an incentive to delay the adoption decision. Lastly, we included the next three years as future periods and explained to the respondents that opting for the outside-good means that they will not adopt any of the brands in the product category, also not in $T > 3$.

We collected data online and distributed a link to our survey to marketing students at Humboldt University Berlin. We also asked the students to forward the link to friends and family members. Each respondent in our sample was asked to make $C = 18$ adoption decisions (structured in 3 blocks, see appendix) and also answer several additional questions about product class experience, socio-demographics, and scales related to the cognitive process during decision-making. 312 respondents completed all choice tasks. We further cleaned the data by requiring that respondents 1) did not own a portable Bluetooth speaker, 2) completed the whole questionnaire, and 3) needed more than 10 minutes (approx. 2.5% were faster than 10 minutes, with a median time of 22.5 minutes) to complete the survey. This resulted in a final data set with 244 respondents with in total 4392 adoption choices. Of these respondents, 70.1% are females, 77.1% are 30 years of age or younger, 93.5% are (bachelor or master) students, and 62.7% have an income of less than 1500 €. Our convenience sample consists, therefore, mainly of younger people, that are well educated and have only a limited budget.

Table 1: Choice Shares Across All Price Scenarios

Brand	June 2017	June 2018	June 2019	June 2020
UE Megaboom	5.6%	10.8%	14.3%	4.0%
JBL Charge 2+	13.9%	17.3%	14.8%	10.3%

As a first check whether the data provides useful information for the dynamic discrete choice model, we analyze the choices descriptively. Only 20.3% of the respondents made choices for one brand and only 14.4% of the respondents adopted products at the same time. Hence, we have a considerable amount of switching across brands and periods in the data. Table 1 summarizes the choice shares for all brands and periods across all choice tasks. We see that while the shares for JBL are fairly similar across the 4 periods, adoptions for UE predominantly take place in period 2 (i.e., June 2019). Also, the shares for JBL are higher than for UE. The higher prices of UE can explain both observations. Lastly, the share for not adopting is 8.8%.

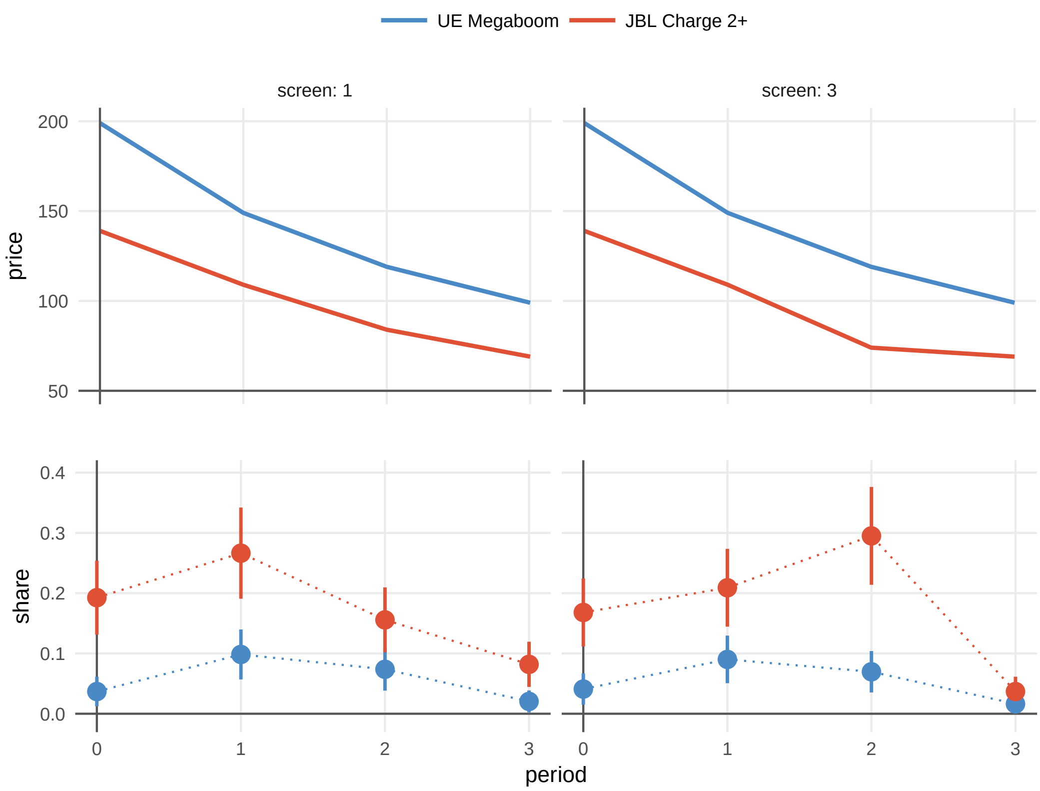

Figure 2: First Intuition Regarding Forward-Looking Behavior

Next, figure 2 shows the price scenarios (upper panel) and the corresponding choice shares with 95% CIs (lower panel). The second price scenario ("screen: 3") only differs from the first one by a lower price for JBL Charge 2+ in period 2; everything else stays the same. This price change predominantly shifts the adoption choice share of JBL from periods 1 and 3 to period 2, which is in line with the dynamic discrete choice model.

To further elaborate on whether respondents are forward-looking, we replicate the analysis in DHJ and look at frequencies of outcomes for particular price scenarios. The price scenarios were built such that in each scenario only one price for one brand is changed compared to a base scenario (i.e., screen 1 in each of the 3 blocks, see appendix). Based on the particular choice of a respondent in the base scenario, we can now classify whether in another price scenario the price of the chosen brand was increased or decreased in an earlier, same, or future period.

Table 2: Model-Free Evidence of Forward-Looking Behavior

	past price		current price		future price	
	decrease	increase	decrease	increase	decrease	increase
n observations	375	153	208	251	559	89
no change	**0.440**	**0.771**	**0.885**	**0.060**	**0.705**	**0.775**
buy same brand earlier	**0.389**	0.000	0.014	**0.016**	0.000	0.000
buy same brand later	0.000	0.000	0.010	**0.295**	**0.147**	0.000
switch to other brand	0.136	0.163	0.087	**0.478**	0.111	0.135
switch to no purchase	0.013	0.059	0.005	**0.133**	0.016	0.011
correctly classified	0.829	0.771	0.885	1.000	0.852	0.775
total			0.862			

Table 2 shows the results. Bold numbers indicate decisions that are consistent with forward-looking behavior. For example, if someone picks a brand in period 1 and the price decreases in a period after period 1 in one of the next screens, we should observe either no change or switching to a later period (for the same brand). The opposite holds in case of a decrease in price for an earlier period. Here we would expect respondents to adopt the same brand earlier (or no change). On average, we see that 86.2% of the decisions of the respondents are consistent with forward-looking behavior. This number matches well the results of the model-free evidence for forward-looking behavior in DHJ.

4 Results

We estimated four different discrete choice models with prices scaled in 100 Euros: 1) the (static) mixed-logit model (MXL), 2) the dynamic MXL model with geometric discounting (DMXL$_G$), 3) the dynamic MXL model with hyperbolic discounting (DMXL$_H$), and 4) the dynamic MXL model with quasi-hyperbolic discounting (DMXL$_{QH}$). Table 3 summarizes the estimation results for these four models. In particular, we report the mean and the standard deviation of the parameter distributions, as well as the log-likelihood values at the maximum and the BIC.

Table 3: Estimation Results

	Model:							
	MXL		DMXL$_G$		DMXL$_H$		DMXL$_{QH}$	
	mean	sd	mean	sd	mean	sd	mean	sd
γ_{JBL}	3.811	4.970	70.159	38.214	38.162	21.502	70.594	36.898
γ_{UE}	3.055	6.212	83.040	45.262	44.533	26.544	82.628	42.612
κ	−0.949	3.923	−50.724	24.570	−22.999	12.335	−52.072	24.963
δ^*			−0.418	1.154			−0.264	1.118
α^{**}					−0.171	1.389		
β^*							10.163	5.124
LL	−7272.851		−4739.681		−5821.667		−4734.945	
BIC	14621.190		9596.788		11760.760		9637.641	

Note: *logistic-normal; **log-normal; sd = $\sqrt{\text{diag}(\Sigma)}$; all coef. significant at $p < 0.01$

All estimated parameters are statistically significant at the 1% level and all models show plausible negative signs for the mean of the distribution of the price parameter. Furthermore, the static MXL model does not fit the data well compared to the other, dynamic MXL models. This is also evident from the low scale of the coefficients (compared to the other models) and the relatively wide distribution of the price coefficient that covers positive values to some extent. The DMXL$_G$ model fits considerably better than the DMXL$_H$ model and it has also a lower BIC than the DMXL$_{QH}$ model. The DMXL$_{QH}$ still fits better than the model with geometric discounting, but the distribution of the present-bias parameter β^* reveals an interesting special case. The estimates are reported on the unconstrained space and because β is bound between 0 and 1, a mean of 10.163 for β^* indicates most of the distribution is concentrated very close to 1. The rather large sd of 5.124 also implies a very small fraction of consumers with a value for

β very close to 0. Thus, the results do not really confirm a superior fit for the quasi-hyperbolic model, but indicate that a mixture of consumers with geometric discounting and perfectly myopic consumers appears to be reasonable for the data at hand. Because the fraction of myopic consumers is very small (about 0.1% with $\beta < 0.01$), we argue that the marginally better fit of the DMXL$_{QH}$ is irrelevant and that the DMXL$_G$ is the best model. DHJ report similar findings, even though their distribution for the present-bias parameter is less extreme.

4.1 Choice Model-Based Discount Factors

For the rest of our analysis we focus on results of the DMXL$_G$ model. Specifically, we now discuss in greater detail the estimated discount factors at the individual level. Figure 3 shows the histogram of the empirical distribution of $\hat{\delta}_i$. The distribution shows almost full support between 0 and 1 (the range is $[0.05, 0.9]$), with a concentration around 0.4. Indeed, the mean of the individual values is 0.43 and the standard deviation is 0.21. Thus, we find rather low discount factors (even for the yearly time-intervals in our study) and a large amount of heterogeneity.

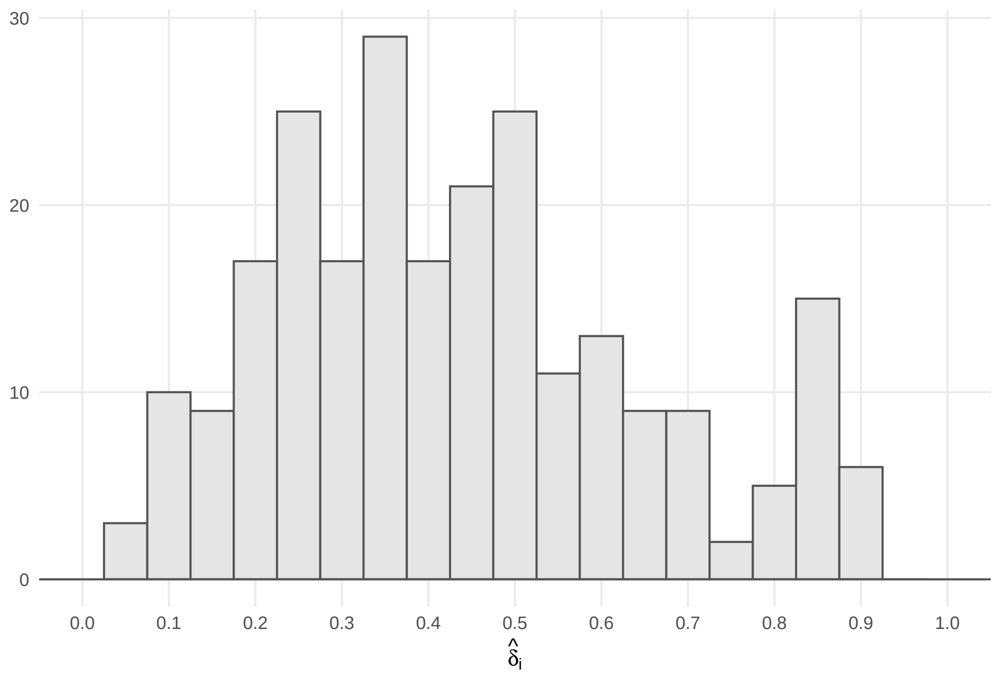

Figure 3: Individual Discount Factors

The importance of heterogenous δ-values becomes also very clear when we look at restricted DMXL$_G$-models with fixed, and therefore, homogenous values for δ. Figure 4 depicts *LL*-values of the fitted models. High and low values for δ lead to a much lower fit compared to the model with the estimated, heterogenous distribution of δ (dashed line), and even a model with $\delta = 0.43$ fits considerably worse.

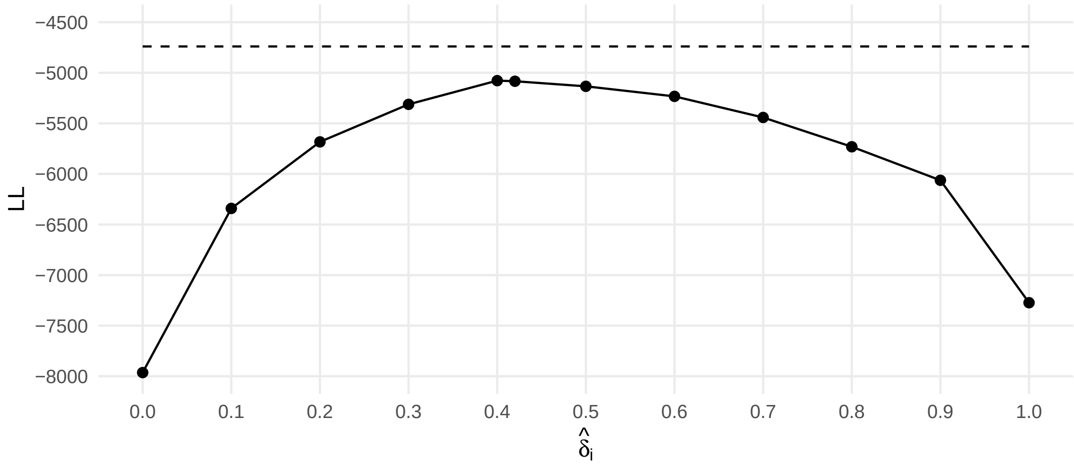

Figure 4: *LL*-Values for the DMXL$_G$ Model with Fixed Discount Factors

Thus, our application replicates the general results of DHJ: We find strong empirical evidence that 1) consumers are forward-looking, 2) the estimated discount factors are considerably lower than typical market interest rates would suggest, and 3) discount factors are very heterogeneous. Lastly, we do not find compelling evidence for (quasi-)hyperbolic discounting of consumers.

4.2 Matching-Based Discount Factors

While our results are in line with the findings of DHJ, the rather low (average) values and high heterogeneity of the estimated discount factors, as well as the weak empirical evidence for present-bias might raise doubts regarding the validity of the results (and hence the particular method for measuring time preferences). To better understand the results, we also included in our questionnaire a second method for the elicitation of discount factors (see Frederick et al., 2002 for an overview). In particular, we used matching tasks where respondents were told to imagine they had won 200 Euros in a lottery and could take the money now or wait for one, two, or three years and receive a larger amount (Thaler, 1981). The respondents were then asked to equate each intertemporal option:

- €200 now = €______ in 1 year
- €200 now = €______ in 2 years
- €200 now = €______ in 3 years

The monetary value and the time frame match our setup for the adoption choice of Bluetooth speakers. However, while the adoption tasks in the choice experiment provide a relevant context and appear to be more realistic, an advantage of matching tasks is that they allow calculating model-free estimates of discount factors for each respondent and period (Urminsky and Zauberman, 2016). The respondent- and period-specific discount factors follow from $\delta_{it} = 200/v_{it}$, where v_{it} is the monetary value that respondent i wants for waiting t years instead of taking the 200 Euros now. Aggregating over respondents yield mean estimates of $\bar{\delta}_1 = 0.72$, $\bar{\delta}_2 = 0.56$, and $\bar{\delta}_3 = 0.45$. While these values look like geometric discounting would also be a reasonable model for discount factors from matching tasks, we estimated all discount functions from section 2.2 with respondent- and period-specific discount factors as the dependent variable using nonlinear least squares.[1]

- Geometric: $f^G(t) = 0.754^t$ (Resid. error = 0.215, BIC = -162.962).
- Hyperbolic: $f^H(t) = 1/(1+0.325 \cdot t)$ (Resid. error = 0.214, BIC = -171.3105).
- Quasi-hyperbolic: $f^{QH}(t) = 0.911 \cdot 0.790^t$ (Resid. error = 0.214, BIC = -164.830).

All estimated parameters are statistically significant at the 1% level. Interestingly, based on matching tasks, the models with (quasi-)hyperbolic discounting outperform the model geometric discounting (i.e., have a lower BIC). However, the fit is only marginally better. Given that our primary motivation for computing matching-based discount factors is the comparison with the model-based discount factors from the previous section, we decide to continue our analysis using the geometric model. Specifically, we compute respondent-specific estimates for the discount factors using the geometric mean: $\hat{\delta}_i = \sqrt[3]{\delta_{i1} \cdot \sqrt{\delta_{i2}} \cdot \sqrt[3]{\delta_{i3}}}$.

Figure 5 shows the histogram of $\hat{\delta}_i$ in the sample. The distribution is now more skewed towards the upper bound, with a mean of 0.73 and a range between 0.25 and 0.99. These results are very similar to findings reported in the literature (see, e.g., Frederick et al., 2002).

4.3 Comparison

Next, we want to compare the results from both methods (i.e., choice model vs. matching tasks). While it was already clear from the previous analyses that the distributions for the discount

[1]We refrain from using hierarchical models because we only have three observations per respondent.

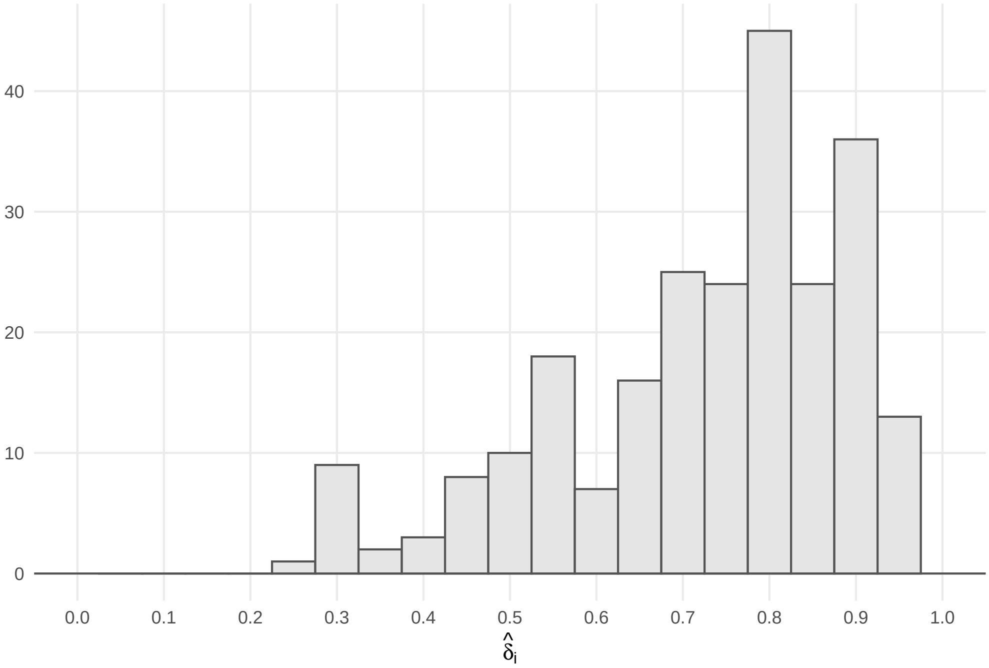

Figure 5: Individual Discount Factors (Matching-Based)

factors somewhat differ, both methods still might lead to similar insights at the respondent-level if discount factors across both methods (but within respondents) are correlated.

Before computing and testing the Pearson correlation, we logit-transform the discount factors: $\hat{\lambda}_{ik} = \ln(\hat{\delta}_{ik}/(1-\hat{\delta}_{ik}))$, with $k \in \{C, M\}$ indicating the two methods (choice model and matching). Correlating δ instead of λ could bias the result towards zero because δ is bounded between 0 and 1. Furthermore, also the potentially large measurement errors of the discount factors at the individual-level can lead to an attenuation of the correlation.[2] To deal with this issue we employed the correction method of Spearman (1904), where the corrected correlation is $\rho = \frac{\text{corr}(\hat{\lambda}_C, \hat{\lambda}_M)}{\sqrt{(R_{\lambda_C} \cdot R_{\lambda_M})}}$. Here the numerator is the Pearson correlation without correction and R_{λ_k} is the reliability coefficient of λ_k. We used the average of the standard errors in both methods to compute these reliability coefficients.

Figure 6 (Panel: A) shows the scatterplot between the transformed discount factors of both methods. We see a positive but not overly strong relationship between both methods. The corrected correlation is 0.195 and hence only small/medium in magnitude. Nevertheless, the value is significant (95% CI [0.053, 0.330]) and hence the results from the choice model are

[2]We computed standard errors for the discount factors using the conditional variance in case of the choice model (see Greene 2012, p. 644) or the simple formula (see, e.g., Harding et al. 2014) in the case of matching. We used the delta method to obtain standard errors for λ.

validated using a different, established method. Panel: B of figure 6 also shows a Bland-Altman plot, where the differences in $\Delta_\lambda = \hat{\lambda}_C - \hat{\lambda}_M$ are plotted against $\frac{\hat{\lambda}_C + \hat{\lambda}_M}{2}$. A correlation does not necessarily imply an agreement between measures and the graph again shows, that matching-based discount factors are larger on average (i.e., $\Delta_\lambda < 0$). However, the graph further clarifies that this difference is not affected by the average values; thus, the level of (dis-) agreement is stable.

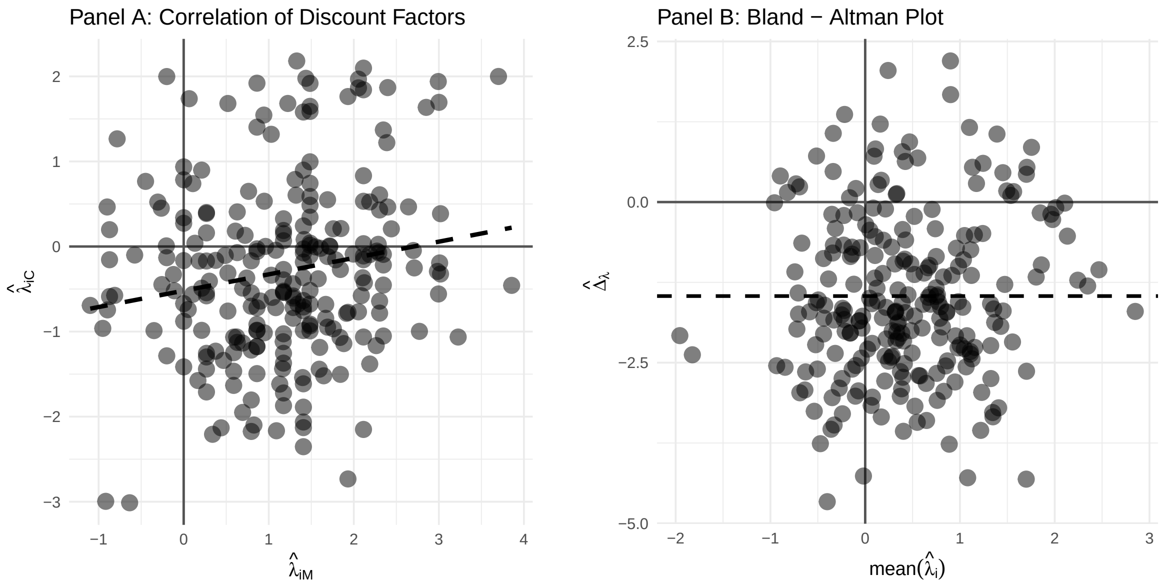

Figure 6: Comparison of Individual Discount Factors

Lastly, to explore whether there are relationships between the level of discounting and observed heterogeneity of the respondents, we regress $\hat{\lambda}_C$ and $\hat{\lambda}_M$ on demographic variables, the survey duration, and the score of the cognitive reflection test (Frederick, 2005). However, we used the 5-item version proposed by Böckenholt (2012). We fitted the linear models using WLS with the inverse of the squared standard errors of the λ_{ik} values as weights.

Table 4 summarizes the regression results with several interesting differences between the discount factors obtained from both methods. In the choice model, higher income is associated with a lower level of patience, which makes intuitive sense. Most other variables, in particular, the ones that might serve as an indicator for more deliberate and rational decision making, do not affect the discount factors. Interestingly, respondents with longer survey durations have lower discount factors, which indicates that low(er) discount factors are not necessarily a result of low attention during the choice experiment. Matching-based discount factors, on the other hand, are indeed positively affected by higher scores of the cognitive reflection test, as in Frederick (2005), or a higher level of education. These respondents might interpret this method of elicitation as a test, and try to give answers that imply more “reasonable” discount factors. As before, longer survey durations are also related to lower discount factors. For matching-based discount factors, income has no significant effect. In both cases, the R^2-values of about 0.11 and 0.12 indicate that the variables explain only some variance in the (transformed) discount factors.

Table 4: Drivers of discount factors

	Dependent Variable:	
	λ_C	λ_M
intercept	0.930* (0.329)	1.616* (0.267)
income (>1000 Euro)	−0.445* (0.128)	0.164 (0.134)
gender (male)	−0.132 (0.135)	0.197 (0.132)
age (26 and older)	0.134 (0.132)	−0.381* (0.143)
edu (BSc or higher)	−0.121 (0.110)	0.420* (0.136)
log(duration)	−0.240* (0.098)	−0.183* (0.071)
CRT score	0.008 (0.047)	0.100* (0.050)
R^2	0.118	0.114

Note: WLS estimates and standard errors in parentheses; * $p < 0.05$

5 Summary and Conclusion

Our results show that consumers are forward-looking. Dynamic models fit the adoption choice data better than static models and models, assuming myopic consumers. Also, the model-free within-subject analysis provides evidence for forward-looking behavior. The discount factors are considerably lower than typical market interest rates would imply (≈ 0.43), and we do not find compelling evidence for hyperbolic discounting (based on the adoption choices). These results are in agreement with the findings from DHJ. In addition, we find that the discount factors obtained from matching tasks (for the same respondents) are considerably higher (≈ 0.73), and mild indications of hyperbolic discounting are present. The correlation of discount factors between both methods is positive and significant, but the magnitude is relatively small. Regression analyses reveal that different variables are related to discount factors in both methods. Higher income affects discount factors in adoption choices negatively, whereas a higher level of education or higher scores in the cognitive reflection test only affect matching-based discount factor positively. This explains to some degree why the correlation between discount factors between both methods is not higher.

The study has several limitations. The adoption choices and the answers in the matching-tasks were not incentivized. Hence, the rather low values of the choice model-based discount factors and the differences across methods might be due to a hypothetical bias. There is a rich literature on mechanisms for incentive-aligned choice-based conjoint analysis (e.g., Ding, 2007), but it is unclear how to adapt these methods such that they would work in the context of adoption choices. Future research should, therefore, analyze the approach of DHJ with consequential adoption choices. Furthermore, we only used a convenience sample that mainly consisted of students. Hence, variation in many relevant demographic variables that are related to time-preferences was limited. Future research should focus on representative samples. Lastly, in DHJ and our study, the empirical evidence of present-biased consumers was weak. Future research should further investigate whether this is a generalizable result for adoption decisions or whether there are particular features of the experimental design that lead to this outcome.

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Appendix

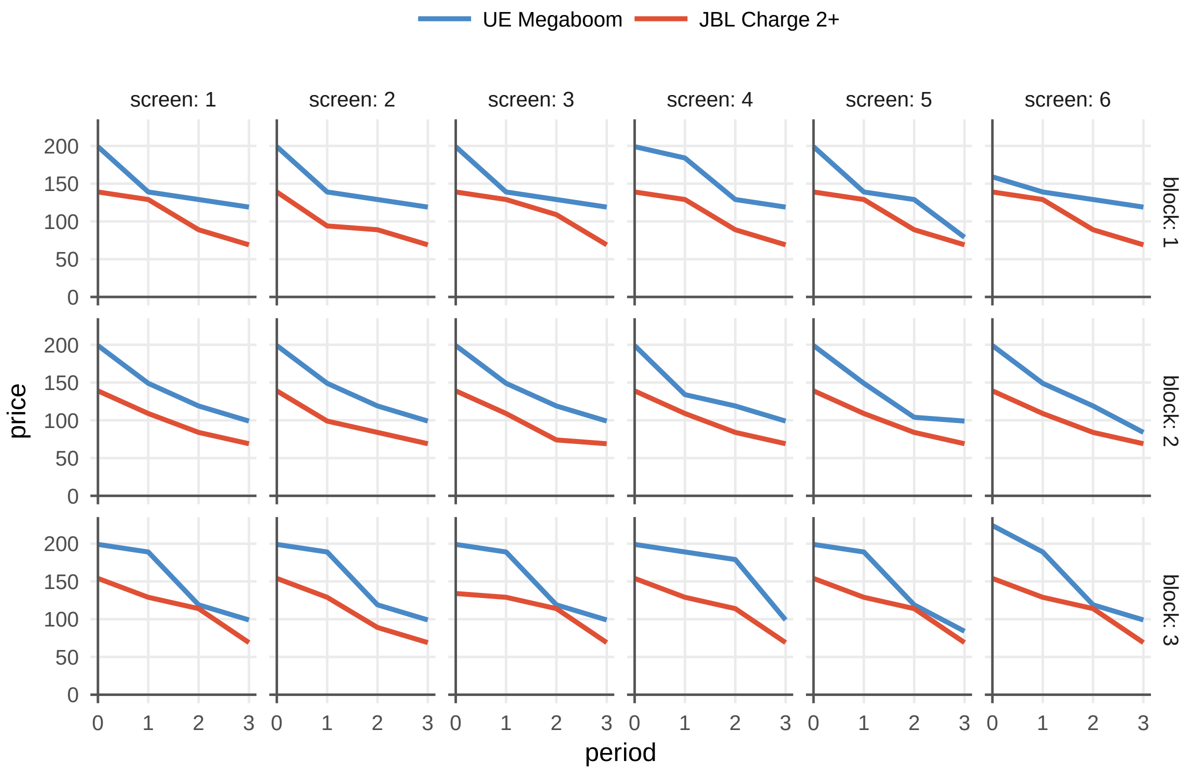

Figure 7: Manipulated Price Time-Series in the Experiment